IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 4, December 2024, pp. 4806~4812
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i4.pp4806-4812

Deep learning model for detection acute cardiogenic pulmonary edema in cases of preeclampsia

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Article Info

Article history:

Received Dec 14, 2023
Revised Mar 24, 2024
Accepted Apr 17, 2024

Keywords:

Acute pulmonary edema
PreEclampsia
ChestXray-14
Deep learning
K-Fold cross validation

ABSTRACT

The physiological changes during the pregnancy period increase the risk of developing pulmonary edema and acute respiratory failure. This condition falls under critical medical emergencies associated with maternal mortality. This study utilized a convolutional neural networks (CNN) architectural model employing chest Xray dataset images. CNN utilizes the convolution process by moving a convolutional kernel of a certain size across an image, allowing the computer to derive new representative information from the multiplication of portions of the image with the utilized filter. To simplify, the vanishing gradient issue occurs when information dissipates before reaching its destination due to the lengthy path between input and output layers. This study was developed model for detection acute cardiogenic pulmonary Edema in pre-eclampsia cases using chest Xray images, implemented using PyTorch, Keras, and MxNet. The validated model achieved its optimum with accuracy 90.65% and binary cross-entropy loss (BCELoss) value of 0.4538. It exhibited an improved sensitivity value of 83.514% using a 5% dataset and a specificity value of 57.273%. This indicates an increase in sensitivity value by 83.514% using a 5% data set and a specificity value of 57.273%. The research results demonstrate an improvement in accuracy compared to several similar studies that also utilized CNN models.

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1. INTRODUCTION

In 2022, the Ministry of Health of the Republic of Indonesia recorded a maternal mortality rate of approximately 183 per 100,000 births higher than that of other Southeast Asian countries [1]. Physiological changes during pregnancy pose a higher risk of developing pulmonary edema and acute respiratory failure. Respiratory failure occurs in 0.2% of pregnancies, primarily during the postpartum period. It can be caused by specific pregnancy-related conditions, such as preeclampsia or peripartum cardiomyopathy. In a closed study conducted in Scotland to identify the risk factors for maternal deaths, pulmonary edema ranked fourth as a cause of maternal mortality. Therefore, immediate management in an intensive care unit is crucial to saving pregnant mothers' lives [1].

Although the incidence of acute pulmonary edema during pregnancy is relatively low, this condition is considered a medical emergency that requires immediate intervention because it can be a cause of maternal mortality [2]. Potential causes of acute pulmonary edema in preeclampsia include angiogenic circulation factors, a decrease in osmotic pressure in the blood, endothelial cell dysfunction, and increased blood vessel pressure with an increased workload on the heart. The importance of rapid and accurate screening in patients experiencing acute pulmonary edema cannot be understated, as it allows doctors to provide a prognosis as quickly as possible. In addition to physical examinations, early screening commonly performed in patients with acute pulmonary edema involves diagnostic tests such as chest XRay. Chest XRay radiography is one of the commonly utilized methods in medical imaging. It plays a crucial role in identifying numerous life-threatening conditions. In the past, thoracic diseases were exclusively assessed by seasoned radiologists [3]. However, advancements in image processing and deep learning methods have paved the way for the automated identification of these ailments [4], [5]. Radiologists examine chest Xray images visually to detect diseases [6], [7]. Many thoracic illnesses exhibit similar patterns, increasing the likelihood of human error in diagnosis and resulting in misdiagnoses.

Artificial intelligence (AI) plays a crucial role in analyzing, visualizing, and interpreting complex medical and health-related data. It encompasses computer algorithms' ability to draw conclusions solely based on input data, known as AI. In healthcare, the primary objective of AI applications is to understand how clinical procedures impact patient outcomes. These applications span various domains, including diagnostics, treatment protocol development, drug research, personalized medicine, patient monitoring, and care delivery. What distinguishes AI technology from traditional healthcare solutions is its capacity to gather, process, and deliver precise results swiftly. This capability is facilitated by machine learning and deep learning algorithms, which enable the recognition of behavioral patterns and the development of logical processes autonomously [5], [8]. Machine learning and deep learning have introduced techniques to enhance the efficiency and speed of this task [9], [10].

The growth of machine learning today has been significantly influenced by the availability of extensive and widely-used datasets [11]. In 2019, researchers made medical information mart for intensive care-chest X-ray (MIMIC-CXR), a substantial publicly accessible collection of chest radiographs [12]–[15]. This current study extends upon the previous research by creating a shared and clinically relevant machine learning task along with an assessment framework that includes baseline performance measurements. This framework will serve as a reference point for future advancements in algorithms designed to assess the severity of for detection acute cardiogenic pulmonary edema from chest radiographs. Several reviews have been published that discuss the utilization of deep learning techniques in the analysis of medical images to detect various diseases. Nowadays many research conducted a method focusing on the application of convolutional neural networks (CNN) and other deep learning methods for identifying COVID-19 using chest X-ray images that obtained good accuracy in classification [16], [17]. Also, they introduced and discussed various ChestXray-14 COVID-19 datasets and highlighted numerous architectural approaches designed to automate COVID-19 detection.

Chandrasekar [18] delved into the use of deep learning techniques for detecting coronavirus in ChestXray-14 images. The review outlined multiple papers that presented novel deep learning methods for feature extraction and the identification of coronavirus. Additionally, they introduced the ChestXray-14 coronavirus datasets employed in these studies and evaluated the performance of deep learning models. Shyni and Chitra [19] conducted a comparative study that examined preprocessing and deep learning techniques employed for the automatic detection of COVID-19 in X-ray and computed tomography (CT) images.

Naz *et al.* [20] proposed a method based on CNN and transfer learning to automatically identify pulmonary conditions such as edema, tuberculosis, nodules, and pneumonia from chest X-rays. Notably, pneumonia, including that induced by COVID-19, poses a significant threat to health. Thus, radiographs of COVID-19 cases were incorporated into the diagnostic process. Approach utilized the ResNet50 neural network, which underwent extensive training using both the COVID-CT dataset and the COVIDNet dataset. According to Saito *et al.* [21], the latest research findings indicate that CNN models show an improvement in identifying pulmonary artery wedge pressure from chest X-ray images in heart failure patients.

We found that a correlation between the AI framework and chest radiographs. The CNN method introduced in this study exhibits significantly higher accuracy rates for chest Xray for detection acute cardiogenic pulmonary edema. This study explores a CNN model architecture designed for the subject-specific detection of acute pulmonary edema in cases of preeclampsia. In contrast, numerous prior studies focused solely on creating models for the detection of common diseases like pneumonia in chest X-Ray images.

The primary contributions of our study encompass: i) an innovative 3-layer CNN architecture for the specific cases detection of acute pulmonary edema of preeclampsia, and ii) cutting-edge neural network designed for visual object recognition, specifically addressing the accuracy decline caused by the vanishing gradient problem in complex neural networks. Following this introduction, the subsequent sections of our research are structured as follows: the section 2 elaborates on our proposed methodology for detection acute cardiogenic pulmonary edema. This is succeeded by the section 3 which provides exhaustive details regarding our experimental setup utilizing both standard datasets. Lastly, the section 4 encapsulates our conclusions.

2. METHOD
2.1. Dataset

The study's CNN architectural model made use of ChestXray-14 images obtained from the publicly accessible ChestXray-14 dataset. This dataset, which can be accessed through the National Institutes of Health's Clinical Center, a renowned clinical research hospital based in Maryland, United States, stands out as the most extensive collection of ChestXray-14 front view images available to the general public. The tally of confirmed cases of pulmonary edema stood at 2,303, factoring in the possibility of duplicate patient data within the existing pathology labels. The approach employed in the division is identical to the one depicted in Figure 1 [22], [23]. To access comprehensive information about licensing terms and citation requirements for this dataset, you can consult the the cancer imaging archive (TCIA) datasets via cloud storage, BigQuery, or utilize the National Institutes of Health (NIH) clinical center's cloud healthcare active pharmaceutical ingredient (API) [24]. Obtaining specific datasets poses challenges, particularly in acquiring chest X-Ray images from patients diagnosed with acute cardiogenic pulmonary edema, especially in cases of preeclampsia.

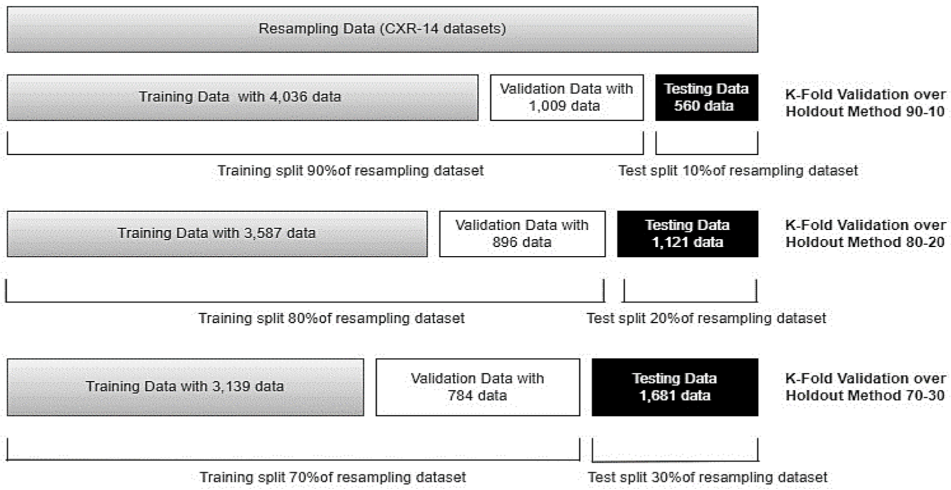

Figure 1. Step holdout validation method

2.2. DenseNet convolutional neural network procedure
2.2.1. Preparation process

In the initial phase of preparation, the first task is to analyze and customize the deep learning framework to suit the existing resources. In this study, we used Phyton library: PyTorch: derived from the Torch library, primarily employed in applications like computer vision; Keras: Python interface for training and deploying deep neural networks; and MxNet: library is portable and capable of scaling to multiple GPUs and machines. The dataset is divided into three main folders (train, test, val) and includes subfolders for each image category (acute cardiogenic pulmonary edema/normal) [25]. The overall process for DenseNet-CNN is shown in Figure 2.

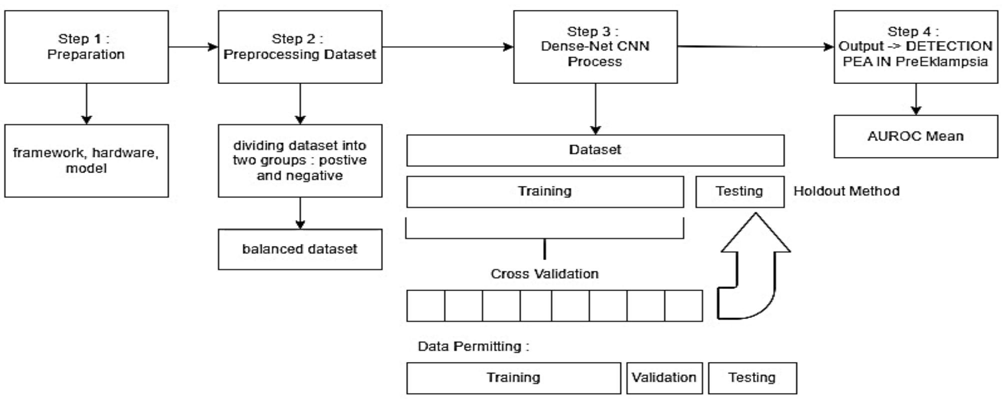

Figure 2. DenseNet-CNN procedure

2.2.2. Preprocessing data

The process in data preprocessing starts with importing the necessary libraries, followed by importing the dataset and reading the image dataset. In this section, we will attempt to visually understand some of the images provided to us for building the classifier for each class. The process concludes with preprocessing the labels. Here, we take the labels and transform them into a clearer format. The initial step involves examining the distribution of findings and then converting them into simple binary labels [26].

Here we take the labels and make them into a clearer format. The ChestXray-14 edema label itself-label 0 to represent negative instances and label 1 represents positive instances. Changes to the algorithm applied to the ChestXray-14 acute cardiogenic pulmonary edema dataset led to an underfit model due to imbalanced data. To tackle this issue, we conducted a re-sampling of the ChestXray-14 dataset for generating valid results. The re-sampling process began 5% reduced dataset, which included positive label and a randomly negative label for detection acute cardiogenic pulmonary edema labels [27].

Using a CNN algorithm on an imbalanced dataset poses the risk of an underfit model, especially in generating false negatives when the dataset remains unaltered. To address this concern, a dataset resampling procedure was implemented [25], [28]. In this research, the approach included the implementation of cross-validation. Initially, 5% of the total data, comprising all positive cases and a random selection of negative cases, was chosen. Subsequently, the data was distributed using a combination of holdout validation and k-fold cross-validation techniques, with the objective of enhancing the model's performance quality, as recommended in [18]. Data splitting occurred after the completion of the data selection process, resulting in the division of the data into three parts: training, validation, and testing, with respective percentages of 70%, 10%, and 20%.

2.2.3. Dense-Net convolutional neural network process

Subsequently, experiments and validation were conducted utilizing the ChestXNet scripts sourced from the GitHub repository portal. This research leveraged the PyTorch deep learning framework. Regarding the selected scripts, several environmental components for the deep learning framework required initial preparation, as detailed in [11]. The optimization algorithm employed was Adam, utilizing standard parameters for efficient output. Specifically, the learning rate was configured to 0.0001, with a weight decay of 1e-5, and the chosen loss function was cross-entropy loss. Following the experimentation phase, the testing stage commenced to produce area under the receiver operating characteristics (AUROC) performance metrics for acute cardiogenic pulmonary edema pathology within the ChestXray-14 dataset.

The AUROC performance achieved at this preparatory stage was subsequently compared with the results documented in [29]. In their journal, serving as a reference for the continuation of the research implementation stage. AUROC, a performance metric employed for assessing classification models, is particularly useful when predicting the probability of a binary outcome. In the context of health or clinical risk prediction models, AUROC quantifies the likelihood that a randomly selected patient who has experienced an event will possess a higher predicted risk score compared to a randomly selected patient who hasn't experienced the event [29].

2.3. Model of DenseNet convolutional neural network

In this study, we employed a DenseNet-CNN to address the accuracy decline and implemented this model using PyTorch, Keras, and MxNet. The constructed CNN architecture offers advantages improved the accuracy. The DenseNet CNN architecture accomplishes this by intricately interconnecting each layer with others in a feed-forward manner [28], [30]. The architecture for proposed methodology is shown in Figure 3.

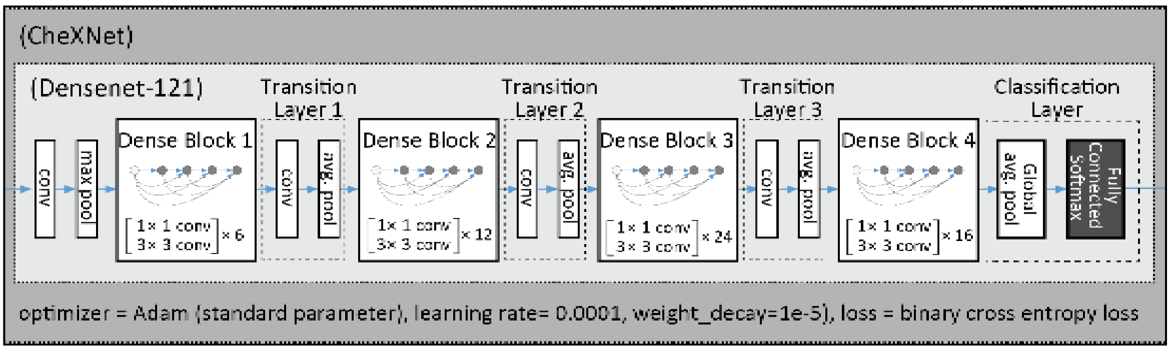

Figure 3. Layer architecture DenseNet CNN architecture for disease abnormality detection for detection acute cardiogenic pulmonary edema

The parameters include the learning rate, which calculates the correction values for the weights between layers in the architecture, set at 0.0001. The Adam optimizer works to maintain per-parameter learning, effectively enhancing the model's performance. Holdout validation approach is then followed by k-fold, identifying the most optimal accuracy from the holdout validation method, and subsequently applying the k-fold method to reduce bias during the testing phase.

3. RESULTS AND DISCUSSION

The results on 5% ChestX-ray14 dataset are shown in Table 1, with a graphical image of accuracy and BCELoss for each epoch batch shown in Figures 4 and 5. The graphical achievement of model accuracy shown in Figure 4 and graphical of BCELoss for each epoch batch is shown in Figure 5. CNN models exhibit stochastic behavior, meaning that each instance of fitting the same model to the same dataset may yield varying predictions and consequently display different overall performance. Evaluating the model relies on a methodology for estimating model proficiency, which involves controlling for model variance. This approach produces differing outcomes when the identical model is trained on disparate datasets, employing k-fold cross-validation. Another approach involves assessing the skill of a stochastic model while controlling for model stability. This method demonstrates varying outcomes when the same model is trained on identical datasets. It entails repeating the evaluation experiment of a non-stochastic model multiple times and subsequently calculating the average of the estimated model skill, commonly referred to as the mean. The ROC curve results of the two models are presented in Table 2.

Table 1. The results on 5% of the ChestX-ray dataset14

Methods	Accuray of each fold (%)	Model accuracy (%)
K-Fold-1	89.57	90.65 (+/-1.62)
K-Fold-2	90.23	
K-Fold-3	90.46	
K-Fold-4	90.49	
K-Fold-5	90.65	
K-Fold-6	89.65	
K-Fold-7	90.27	
K-Fold-8	90.08	
K-Fold-9	89.83	
K-Fold-10	89.03	

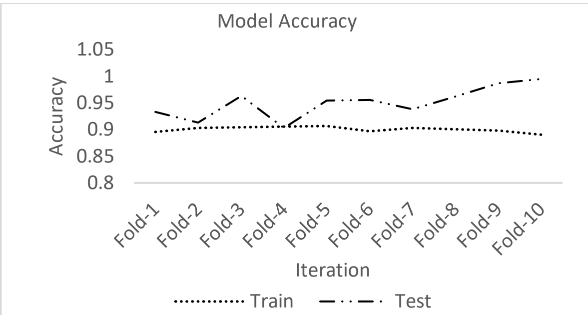

Figure 4. Graph of accuracy k-fold on 5% dataset

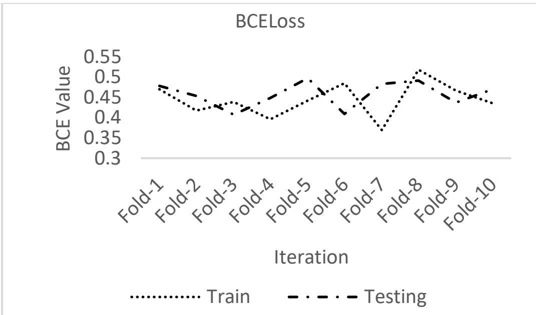

Figure 5. Graph of BCELoss dataset

Table 2. F-measure and AUROC mean for the 100% dataset

Training Dataset							
Condition						Confusion matrix	
	Precision	Recall	F-Measure	ROC area	Class	a	b
Normal (100% data)	0.951	0.93	0.973	0.713	N	1909	101
	0.713	0.717	0.744	0.713	P	175	75
	0.862	0.878	0.858	0.713	Average		

We findings reveal that the DenseNet-CNN model, derived from downsampling the ChestX-ray14 dataset to a more 5% of its original size, has proven to be a reliable model. Transitioning to the next stage, we present the best model file obtained. The model proposed in this study demonstrates a notably higher proportion of accuracy in 90.65%, BCELoss value of 0.4538. It exhibited an improved sensitivity value of 83.514% using a 5% dataset and a specificity value of 57.273 when trained on just 5% of the dataset.

The suggested models are assigned a value of k=10. For every k value, the dataset will be divided into training (70%) + validation (10%) = 80% and testing =20%, with the testing performance recorded based on the chosen metric (accuracy, in this case). Subsequently, the average performance is calculated to present the ultimate outcome. The execution of the 10-fold cross-validation and the experimental findings are depicted in Table 3. Table 3 also provides a comparison between our proposed techniques and recent studies.

Table 3. Comparasion of recent works with our proposed methods

Reference	Proposed technique	Result
[31]	ResNet34, ResNet50, DenseNet169, VGG-19, InceptionResNetV2 & RNN	84% of average accuracy on pneumonia detection cases.
[21]	Regression CNN for elevated pulmonary artery wedge pressure (PAWP)	Elevated PAWP (≥ 18 mm Hg) Model was comparable to the AUC of an experienced cardiologist (0.86 vs. 0.83, respectively; P = 0.24).
[16]	CNN	Found to recognize older subjects from younger ones rather than younger subjects from older ones.
[17]	MobileNetv2	Accuracies of 97.59%
[20]	ResNet50 neural network for COVID-CT and COVIDNet	Accuracies of 93% and 97%, respectively
Proposed CNN Model	New architecture of CNN	Accuracy 90.65%

Analysis of our findings suggests that this research not only enhances classification accuracy but also offers valuable explanations for pulmonary diseases using advanced deep learning techniques. Such insights could aid radiologists in automatic disease detection and explanation, facilitating clinical decision-making and early diagnosis and treatment of pulmonary conditions. However, further and in-depth studies may be needed to confirm its especially regarding model trained with 5% of the reduced dataset. Our study demonstrates that achieving high accuracy in detecting for detection acute cardiogenic pulmonary edema pathology is more robust compared to other methods but has a low specificity value. Future research efforts could explore the utilization of additional datasets and the development of a model capable of autonomously adjusting the bandwidth parameters of weighting functions during training, thereby enhancing performance.

4. CONCLUSION

Our findings provide an innovative approach utilizing location-aware DenseNet architecture for detection acute cardiogenic pulmonary in cases of preeclampsia and validate the model using K-fold cross-validation. This method effectively utilizes high-resolution data and integrates spatial information of pathologies to enhance classification accuracy. The experimental outcomes demonstrate enhanced accuracy compared to existing state-of-the-art methods through the implementation of the proposed CNN architecture. The algorithm is demonstrated to be effective in this context, the most optimal modification of the DenseNet architecture was obtained to detect acute cardiogenic for detection acute cardiogenic pulmonary edema in cases of preeclampsia and validate the model using K-fold cross-validation in accuracy 90.65%, BCELoss value of 0.4538 which was achieved by the 5th fold. A better sensitivity value was obtained from the 5% dataset of 83.514% and a specificity value of 57.273%.

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